

MODELING AND SIMULATION OF RELIABILITY & MAINTAINABILITY PARAMETERS FOR REUSABLE LAUNCH VEHICLES USING DESIGN OF EXPERIMENTS

Resit Unal
Old Dominion University, Norfolk, VA 23529

W. Douglas Morris, Nancy H. White and Roger A. Lepsch
NASA Langley Research Center, Hampton VA 23681

Abstract: This paper describes the development of a methodology for estimating reliability and maintainability distribution parameters for a reusable launch vehicle. A disciplinary analysis code and experimental designs are used to construct approximation models for performance characteristics. These models are then used in a simulation study to estimate performance characteristic distributions efficiently. The effectiveness and limitations of the developed methodology for launch vehicle operations simulations are also discussed.

Introduction

For future missions only those vehicle launch systems which are considered affordable and economical will be selected due to budget constraints and rising global competition. The need for cost effectiveness dictates that space transportation systems are designed not only focused on performance and acquisitions but also for producibility, operability, maintainability and supportability. Such an environment calls for innovative design approaches, which address all of the lifecycle phases and the uncertainties early in the conceptual design phase.

Modeling Operational Requirements

A significant portion of life-cycle costs for aerospace systems is generated during the

operations and support (O&S) phase. Studies indicate that O&S costs for complex systems can account for 60-80 % of the total lifecycle costs (Griffin, 1988). Clearly, O&S costs are largely determined by decisions made during conceptual design. As a result, operational considerations of the effects of these decisions need to be modeled and studied early in the design phase. This is a challenging task since O&S requirement estimation for new launch vehicle concepts is characterized by high uncertainty, mainly due to lack of data. Therefore operational activities are typically studied using stochastic methods and simulation.

Operational requirements can be linked to the concept through its reliability and maintainability (R&M) characteristics. The R&M characteristics for a future launch vehicle design can be estimated based on comparisons to existing systems. For this purpose, a reliability and maintainability analysis and estimation tool (RMAT) which is based on comparability to support requirements for current operational aircraft and launch vehicles has been developed (Ebeling & Donohue, 1994; Morris, White & Davis, 1995). Using RMAT, operational characteristics such as mission completion reliability, maintenance actions per mission, manpower and support requirements can be estimated for a particular vehicle concept and mission scenario.

The vehicle operational characteristics can then be used as input for a discrete event simulation to model proposed operational scenarios and to estimate cost for the concept under study. Insight to the effects of the uncertainty in these characteristics can be obtained if the uncertainty is defined or estimated as a probability distribution for use with the model

This paper describes the development of a methodology for estimating reliability and maintainability probability distributions for a test case reusable launch vehicle design. RMAT and determinant optimal (D-optimal) experimental designs are used to sample the design space efficiently for model building and a Monte Carlo simulation algorithm is used for conducting the simulation studies. The methodology has the following steps:

1. Determine the Significant Parameters

Since RMAT has a very large number of input parameters, those that can have a significant impact on results were identified for the test case vehicle. An initial analysis and was conducted to determine the sensitivity of the R&M performance (output) characteristics given in Exhibit-1 to the variations of the input parameter values.

1. Mission completion reliability
2. Mission completion subsystem reliability for insulation tiles
3. Mission completion subsystem reliability for landing gear
4. Maintenance actions per mission
5. Total maximum manpower
6. Weighted avg. ground processing days.

Exhibit-1. Performance Characteristics

As a first step, a brainstorming study was conducted to identify the input parameters that can have a significant

impact on the output performance characteristics based on expert judgement. To reflect the uncertainty, a range of values were determined for each of the nine parameters identified. RMAT was run by varying the input parameters one parameter at a time within the range determined. The results showed significant sensitivity to variations in the following six input parameters (Exhibit-2):

- 1) Technology year (TYR)
- 2) Launch factor (LFTR)
- 3) Weibull shape parameter (WEIB)
- 4) Mission No. for rel.growth (MNRG)
- 5) Critical failure rate Tiles (CFTL)
- 6) Critical failure rate for landing gear (CFLA).

Exhibit-2. Input Parameters

The next step was to construct response surface models that approximate RMAT output characteristics as a function of the six input parameters.

2. Response Surface Modeling

RMAT is a complex operational analysis code requiring expert user inputs. As it currently stands, it is difficult to use directly for optimization and simulation studies without integration to other analysis codes. If however, one can express operational performance characteristics such as mission completion reliability as a function of the input parameters in a simplified model that approximates RMAT, simulation analysis can be conducted very rapidly. Therefore, response surface methodology (RSM) was utilized to obtain polynomial models that approximate the functional relationships between performance characteristics and input parameters. These approximation models, called response surface models, can then be used for efficient system level analysis, optimization and rapid sensitivity

simulations. A second order response surface model of the form given below (Equation-1) has been commonly used in RSM since in many cases it may provide an adequate approximation, especially if the region of interest is sufficiently limited.

$$Y = b_0 + b_1 x_1 + b_{11} x_1^2 + b_{12} x_1 x_2 + b_{22} x_2^2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 + b_{33} x_3^2 + b_{14} x_1 x_4 + b_{24} x_2 x_4 + b_{34} x_3 x_4 + b_{44} x_4^2 + b_{15} x_1 x_5 + b_{25} x_2 x_5 + b_{35} x_3 x_5 + b_{45} x_4 x_5 + b_{55} x_5^2 + b_{16} x_1 x_6 + b_{26} x_2 x_6 + b_{36} x_3 x_6 + b_{46} x_4 x_6 + b_{56} x_5 x_6 + b_{66} x_6^2$$

In Equation-1, the x_i terms are the input variables that influence the response Y (performance characteristic such as mission completion reliability), and b_0 , b_i , and b_{ij} are estimated model coefficients. The cross terms represent two-parameter interactions, and the square terms represent second-order non-linearity.

This second-order model can be constructed efficiently by utilizing design-of-experiments (DOE) techniques for sampling the design space. Some of these are Taguchi methods (Phadke, 1989), central composite designs (Myers, 1971, Khuri and Cornell, 1987) and minimum point D-Optimal designs (Craig, 1978). These methods have been applied in many launch vehicle multidisciplinary design optimization problems (Lepsch, Stanley and Unal, 1995; Unal, Stanley and Lepsch, 1996; Unal and Lepsch, 1998). Current research and applications indicate that "Augmented D-Optimal Designs" may be the best approach for response surface model building using computerized analysis codes (Unal, Lepsch and McMillin, 1998).

Therefore, an augmented D-Optimal design was constructed for this study which is partially given in Exhibit-3 (JMP®, 1992). With this design matrix, the six input parameters are studied at three levels (values) as represented in coded form by, -1, 0 and +1 with 42 experiments (RMAT runs in this case).

A full-factorial study, where all parameter combinations are investigated, would have required 729 experiments (3^6).

	CFTL	CFLA	WEIB	MNRG	LFTR	TYR
1	-1	-1	-1	-1	-1	+1
2	-1	-1	-1	-1	+1	-1
3	-1	-1	-1	+1	-1	-1
4	-1	-1	-1	+1	+1	+1
5	-1	-1	+1	-1	-1	-1
6	-1	-1	+1	-1	+1	+1
7	-1	-1	+1	+1	-1	-1
8	-1	-1	+1	+1	+1	+1
9	-1	+1	-1	-1	-1	-1
10	-1	+1	-1	-1	+1	+1
11	-1	+1	+1	-1	-1	-1
12	-1	+1	+1	-1	+1	+1
13	-1	+1	+1	+1	-1	-1
14	-1	+1	+1	+1	+1	+1
15	-1	+1	-1	+1	-1	-1
16	-1	+1	-1	+1	+1	+1
17	-1	+1	+1	+1	-1	-1
18	-1	+1	+1	+1	+1	+1
19	-1	-1	-1	-1	-1	-1
20	-1	-1	-1	-1	+1	+1
21	-1	-1	-1	+1	-1	-1
22	-1	-1	-1	+1	+1	+1
23	-1	-1	+1	-1	-1	-1
24	-1	-1	+1	-1	+1	+1
25	-1	-1	+1	+1	-1	-1
26	-1	-1	+1	+1	+1	+1
27	-1	+1	-1	-1	-1	-1
28	-1	+1	-1	-1	+1	+1
29	-1	+1	+1	-1	-1	-1
30	-1	+1	+1	-1	+1	+1
31	-1	+1	+1	+1	-1	-1
32	-1	+1	+1	+1	+1	+1
33	-1	+1	-1	+1	-1	-1
34	-1	+1	-1	+1	+1	+1
35	-1	+1	+1	+1	-1	-1
36	-1	+1	+1	+1	+1	+1
37	-1	-1	-1	-1	-1	-1
38	-1	-1	-1	-1	+1	+1
39	-1	-1	-1	+1	-1	-1
40	-1	-1	-1	+1	+1	+1
41	-1	-1	+1	-1	-1	-1
42	-1	-1	+1	-1	+1	+1

Exhibit-3: D-Optimal Experimental Design

Once the RMAT runs at the values specified by the D-Optimal design were completed, data was generated for the five output performance characteristics. Using this data, multiple least squares regression analysis was conducted to construct second order (Equation 1) response surface models for the five output performance characteristics. As an example, the second-order response surface model for mission completion reliability is given below.

Mission Completion Reliability =

$$0.973343 - 0.001178*(CFTL) - 0.001079*(CFLA) - 0.001037*(WEIB) + 0.019334*(MNRG) - 0.027490*(LFTR) + 0.011388*(TYR) + 0.004135*(CFTL)^2 - 0.002556*(CFLA)*(CFTL) - 0.001967*(CFLA)^2 + 0.000334*(WEIB)*(CFTL) - 0.001382*(WEIB)*(CFLA) - 0.004517*(WEIB)^2 + 0.000459*(MNRG)*$$

$$\begin{aligned}
& (CFTL) + 0.001303 * (MNRG) * (CFLA) - \\
& 0.000302 * (MNRG) * (WEIB) - 0.009207 * \\
& (MNRG)^2 + 0.001780 * (LFTR) * (CFTL) + \\
& 0.000057 * (LFTR) * (CFLA + 0.000112 * \\
& (LFTR * (WEIB) + 0.013343 * (LFTR) * \\
& (MNRG) - 0.001918 * (LFTR)^2 + \\
& 0.002461 * (TYR) * (CFTL) - 0.002255 * \\
& (TYR) * (CFLA) 0.007261 * (TYR) * (LFTR) - \\
& 0.000389 * (TYR)^2
\end{aligned}$$

This equation proved to be a good approximation to the actual RMAT model (in the range studied) with an R Square value of 0.985 and Mean Square Error of 0.000062. Similarly good approximations were obtained for, maintenance actions per mission, total maximum manpower and weighted average ground processing days. However model predictions for Subsystem Reliabilities were not as good. The problem here appeared to be arising from the selection of a very wide range for the reliabilities studied for these subsystems.

3. Monte Carlo Simulation

In the next step, the four response surface models for mission completion reliability, maintenance actions per mission, total maximum manpower and weighted average ground processing days were utilized to conduct a Monte Carlo Simulation study. A symmetrical triangular distribution was assumed for the six input parameter values with the most likely value being the midpoint of the range chosen for the RSM study. A personal-computer based simulation software was utilized to run a Monte Carlo simulation that sampled from the input parameter distributions to compute values for the output performance characteristics. The output frequency and cumulative distributions were plotted using this data generated by the simulation.

Results and Conclusions

Since the simplified response surface equations were utilized for the simulation studies rather than the direct use of the analysis code, the analyses were conducted rapidly without the need for any software integration. The results showed that the distribution shapes for the four operations performance characteristics had skewed distributions. This can have important implications in terms of the operational requirements since a higher (or lower) value is more likely than the computed average value and can affect the outcome of an operational scenario.

These results also open other avenues of application of the methodology in the operations area. As an example, response surface models for different types of vehicles can be developed for use with cost estimating models that can simplify the use of RMAT for non-experienced users. Another application is that this approach can be utilized for operations requirements optimization. Ultimately, the response surface models may be utilized for integrating operational considerations to the overall conceptual vehicle design through the use of mathematical programming methods.

References

J.A. Craig, "D-Optimal Design Method: Final Report and User's Manual," USAF Contract F33615-78-C-3011, FZM-6777, General Dynamics, Fort Worth Div., 1978.

Ebeling, C.E., and C.B. Donohue, "Integrating Operations and Support Models During Conceptual Design", *Annual Report*, Grant No. NAG1-1-1327 (1994).

JMP® *Design User's Guide*, SAS Institute Inc, Cary, NC, (1992).

Griffin, J.J., "Whole Life Studies: A

Defense Management Perspective,” Engineering Costs and Production Economics, No.14 (1988) pp. 107-115.

Khuri, A.I. and J.A. Cornell, *Response Surfaces: Designs and Analyses*, Marcel Dekker Inc., New York (1987).

Lepsch, R.A., D.O. Stanley and R. Unal, "Dual-Fuel Propulsion in Single Stage Advanced Manned Launch System Vehicle,” *Journal of Spacecraft and Rockets*, Volume 32, Number 3 (1995), pp. 417-425.

Morris, W.D., N. H. White and W.T. Davis, “Defining Support Requirements During Conceptual Design of Reusable Launch Vehicles,” *American Institute of Aeronautics and Astronautics Space Programs and Technologies Conference, Paper No.AIAA-95-3619* (September 1995).

Morris, W.D., N. H. White and R.G. Caldwell, “HL20 Operations and Support Requirements for the Personnel Launch System Mission,” *Journal of Spacecraft and Rockets*, Vol. 30, No. 5 (1993), pp. 597-605.

Myers, R.H. *Response Surface Methodology*, Virginia Commonwealth University, Allyn and Bacon Inc., Boston Mass. (1971).

Phadke, S. M., *Quality Engineering Using Robust Design*, Prentice Hall, Englewood Cliffs, NJ (1989).

@Risk, *Advanced Risk Analysis for Spreadsheets*, Guide to Using, Palisade Corporation, Newfield, NY (1997).

Unal, R, R.A. Lepsch and, M.L. McMillin, “Response Surface Model Building And Multidisciplinary Optimization Using D-Optimal Designs,” *7th Annual AIAA/NASA/ISSMO Symposium*

on Multidisciplinary Analysis and Optimization, Paper No: AIAA-98-4759 (September 1998).

Unal, R., D.O. Stanley and R.A. Lepsch, "Parametric Modeling Using Saturated Experimental Designs," *Journal of Parametrics*, Volume XVI, Number 1 (Fall 1996), pp. 3-18.

Biographies

Resit Unal is an associate professor of Engineering Management at Old Dominion University, Norfolk, Virginia. He is a member of the American Society for Engineering Management, American Institute of Aeronautics and Astronautics and International Society of Parametric Analysts.

W. Douglas Morris is an aerospace engineer in the Vehicle Analysis Branch, Space Systems and Concepts Division at NASA Langley Research Center. He is a member of the American Institute of Aeronautics and Astronautics.

Nancy H. White is an aerospace engineer in the Vehicle Analysis Branch, Space Systems and Concepts Division, at NASA Langley Research Center.

Roger A. Lepsch is an aerospace engineer in the Vehicle Analysis Branch, Space Systems and Concepts Division at NASA Langley Research Center. He is primarily responsible for performing mass and size estimates of advanced launch vehicles. He is a member of the American Institute of Aeronautics and Astronautics.